This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2657820, IEEE Access

When Mobile Crowd Sensing Meets Traditional Industry

Lei Shu†, Yuanfang Chen†✉, Zhiqiang Huo†, Neil Bergmann‡, Lei Wang§
†Guangdong Provincial Key Laboratory on Petrochemical Equipment Fault Diagnosis,
Guangdong University of Petrochemical Technology, Maoming, China
‡School of Information Technology and Electronic Engineering, The University of Queensland, Australia
§School of Software, Dalian University of Technology, Dalian, China
Email: {lei-shu, yuanfang.chen.tina, zhiqiang.huo}@outlook.com, bergmann@itee.uq.edu.au, lei.wang@dlut.edu.cn

***Abstract*—With the evolution of mobile phone sensing and wireless networking technologies, mobile crowd sensing (MC-S) has become a promising paradigm for large-scale sensing applications. MCS is a type of multi-participant sensing that has been widely used by many sensing applications because of its inherent capabilities, e.g., high mobility, scalability, and cost effectiveness. This paper reviews the existing works of MCS and clarifies the operability of MCS in sensing applications. With wide use and operability of MCS, MCS's industrial applications are investigated based on the clarifications of (i) the evolution of industrial sensing, and (ii) the benefits MCS can provide to current industrial sensing. As a feasible industrial sensing paradigm, MCS opens up a new field that provides a flexible, scalable, and cost-effective solution for addressing sensing problems in industrial spaces.**

I. INTRODUCTION

Successful large-scale urban and industrial management relies on the efficient sensing and acquisition of physical information about the surroundings for decision and policy making. Traditional sensing technologies usually leverage distributed sensors to acquire environmental information. However, the spatial coverage of the currently deployed sensor networks in the real world is low, and the scalability and mobility of such networks are insufficient. Along with the evolution of industrial requirements on sensing, mobile crowd sensing (MCS) is a potentially effective sensing paradigm. This sensing paradigm has three impressive properties: cost effectiveness, scalability, and mobility [1]. These three features make MCS suitable to be used in industrial applications. However, as a new paradigm, MCS has not yet been formally applied to industry because of the strict requirements for the maturity of technology in industry. In the remainder of this paper, the possibility of MCS to be applied into industry will be investigated.

MCS is a large-scale sensing paradigm which uses the power of users with accompanying smart phones [2]. MCS enables many users to share surrounding information and their experiential knowledge via sensor-enabled mobile phones. Using MCS, the target area of sensing can achieve enough coverage, and such coverage is scalable and cost effective [1]. A broad range of MCS-based applications are thus enabled, and most of the relevant studies have investigated applications in urban spaces, including urban environment monitoring [3], mobile social recommendations [4], public safety [5], traffic control and planning [6], and geospatial information gathering [7]. MCS is also applicable to problems of large-scale industrial environments. In such environments, safety is the major concern [8], and so the solutions and applications must address safety requirements.

This paper reviews the typical existing MCS works in Section II. Regarding the extension of MCS to industrial spaces, potential industrial applications of MCS and corresponding open issues are investigated in Section IV. This investigation is based on analyzing the evolution of industrial sensing and the benefits that MCS can provide, in Section III. The analysis of these benefits emphasizes how MCS meets the requirements of industrial production. Finally, Section V concludes this paper.

II. EXISTING WORKS OF MCS

Some existing MCS applications that have been developed and studied in previous works [9] are classified and listed in Figure 1.

From the perspective of the way of use, existing MCS applications are classified into two categories. The first category includes, for example, personal health monitoring and health care [10], smart city [11], virtual teaching [12], virtual reality (VR) entertainment (PokemonGO) [13], sport experience [14], and social media [15]. The second category includes, for example, environmental monitoring [16], crisis prediction and management [17], geospatial information collection [18], population migration [19], intelligent transportation [20], and urban planning [21].

Mobile phones are carried by people who can move anywhere on foot or by vehicle, so the corresponding sensing modalities can be broadly classified into three categories [22]: *individual sensing* [2], *group sensing* [3], and *community sens-*

Corresponding author: Yuanfang Chen

[1]Increasing or decreasing the number of smart phones helps MCS provide a scalable solution to area coverage. This scalable solution can freely adjust the coverage without other, additional investment.

[2]Data collected for personal use only; that is, not shared with other people.

[3]Data collected for sharing with a group of people.

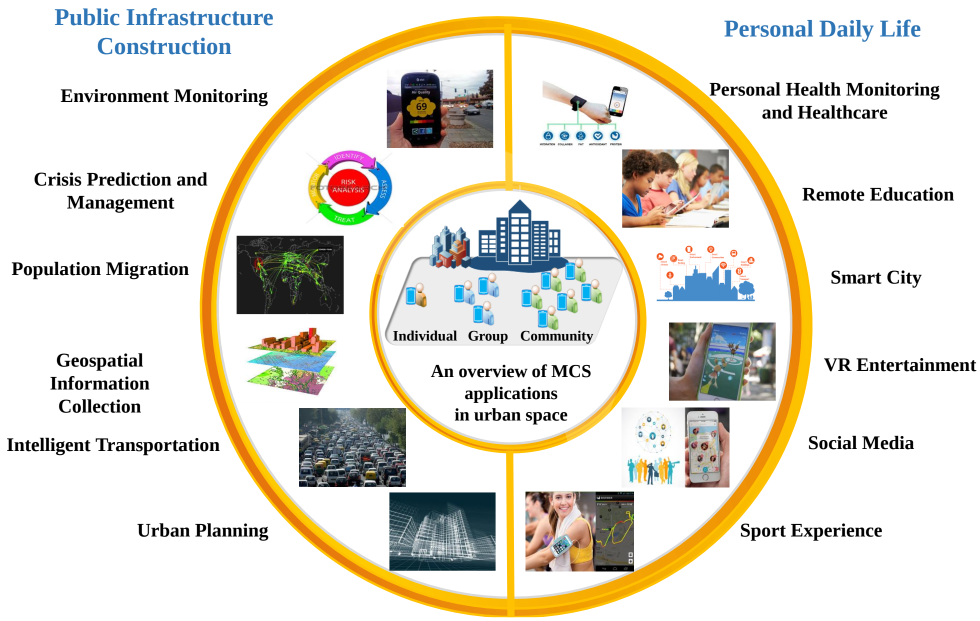


Fig. 1. Existing works of MCS, which are classified into two broad categories: (i) the applications used in personal daily life, and (ii) the applications used in public infrastructure construction.

ing [4], by considering the different types of phenomena being monitored.

- In individual sensing [23], the phenomena being monitored pertain to individuals; for example, the monitoring of individual movement patterns (e.g., running, walking, exercising, and driving). The individual mentioned here is not specific. Considering the sensing from a large number of individuals, this can be seen as crowd sensing. Such sensing enables large amounts of information to be obtained from different individuals and shared among these individuals.
- Group sensing is used to monitor group phenomena that cannot be easily measured by a single individual [24]; for example, in virtual teaching, students' mobile phones are used to sense and share the physical information around them. Through such virtual teaching, students can learn about the customs of different cities and countries.
- Community sensing is used for large-scale monitoring of community phenomena that cannot be easily measured by a special group of people (e.g., students) [25]; for example, intelligent transportation systems. Such systems can sense the congestion of different road segments through the mobile phones carried by drivers, and the cameras installed in the systems, to measure travel speed. Unlike group sensing, there are different groups in community sensing.

Considering the current mobile phone based sensing modalities and existing MCS applications, the research issues for current MCS are summarized as follows:

- Energy Consumption/Saving [26]. How to best manage the energy consumption of MCS data transfer, computing, and sensing by mobile phones.
- Security and Privacy [27]. How to protect sensitive personal and location information.
- Data Trustworthiness [28], MCS Data Quality [29], [30], [1], [31]. The accuracy and coverage of sensor readings impact the reliability and availability of data. If the data have high reliability and availability, they will have high trustworthiness and quality when used to analyze and solve a real problem.
- Incentive Techniques[32]. How to motivate individuals to participate in the sensing process for completing a task. A good incentive mechanism is important to efficiently implement MCS.

Summarizing the typical applications, sensing modalities and research issues, MCS is more focused on a single type of participant (humans) and mobile device (mobile phone).

III. MCS Meets Industry

In industrial spaces, a series of complex processes are involved in the following different industrial stages: industrial production, storage, logistics, marketing, and user feedback. As an emerging sensing paradigm, MCS can be easily used in industrial spaces to solve the problems of the different industrial stages, because of the inherent capabilities of MCS: high mobility and scalability. Moreover, MCS is a kind of cost-effective sensing paradigm. It does not need additional dedicated devices to extend the existing industrial sensing system. Furthermore, MCS can integrate different industrial

[4]Data collected by people from communities, and integrated together to predict global trends.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2657820, IEEE Access

stages, and let them share information, and can integrate human wisdom into machine intelligence.

Figure 2 illustrates the evolution of industrial sensing. In the smart sensing stage, MCS is proposed to achieve the integration of human wisdom and the industrial Internet of Things (IoT) [33].

The evolution of industrial sensing includes four stages: human perception, physical sensing, intelligent sensing, and smart sensing. Starting from the physical sensing stage, sensors are widely used, including recent adoption of wireless sensor networks [34]. As an extension, artificial intelligence (AI) appears in the intelligent sensing stage, with the development of mobile and embedded computing [35]. In this stage, the trend is to add human knowledge and even wisdom into machine intelligence. However, because of the costs and technical limitations of current robots (AI), it is hard to provide the robots with human wisdom. MCS is proposed to achieve the combination of the human knowledge/wisdom and machine intelligence [2]. By this combination, industrial sensing evolves to the smart sensing stage. Compared with traditional urban-space MCS, in industry, the industrial IoT is added to strengthen the machine intelligence [36]. MCS is cost-effective and based on mature technology, and it combines human wisdom and a high degree of scalability. From Figure 2, the evolution of industrial sensing experienced two big stages: in the early stage of industrialization, artificial observation is the main method to sense industry, and then with the birth of sensors in 1821 [37], it opens up the intelligent stage of industry.

An issue that is worthy of further discussion is comparing the relative costs of robots (AI-based sensing) and humans with mobile phones (MCS). From the perspective of typical industrial requirements for sensing, the relative costs can be compared.

A detailed cost comparison is provided in Table I.

Table I lists 11 typical requirements of industrial sensing from four aspects, and the costs of MCS and AI-based sensing are compared upon meeting these requirements. The detailed explanations are as follows:

- Environmental Monitoring. MCS-based environmental monitoring has high scalability in the number of and type of devices, and it can quickly achieve full coverage in an area of interest by relying on the good mobility of human-carried mobile devices. For AI-based sensing, to achieve environmental monitoring, sufficient quantities of robots are necessary to fully cover an interested area. The scalability and mobility of AI-based sensing are based on the performance of robots; for example, compared with static robots, mobile robots perform better.
- Personal Monitoring. MCS-based personal monitoring uses the mobile devices carried by individuals (e.g., pulse-sensor-embedded wrist watch) to obtain physical condition and location information. AI-based sensing is difficult to use for personal monitoring.
- Process Monitoring. There are three stages in an industrial process: production, storage, and logistics. On this basis, quality checking, asset tracking, and location are important requirements in the industrial process.
  - ◦ Quality Checking. For quality checking, MCS is not always possible; for example, as an important part of an assembly line, robots can be easily used to achieve AI-based quality checking, but MCS only has human-carried mobile devices, and if MCS-based quality checking wants is to be implemented, additional components are necessary, e.g., quality scanners need to be embedded into the human-carried mobile devices.
  - ◦ Asset Tracking. Because of the high degree of mobility, MSC is easy to use in asset tracking.
  - ◦ Location. Location information is important and required for process monitoring in industrial s-paces. Using location information, an industrial process can be clearly tracked, and it is clearly known where and what things are happening. MCS is very easy to achieve this using workers, and AI-based sensing also can accomplish it using the robots participating in the production process.
- Product Monitoring. MCS is easy to use for product monitoring.
  - ◦ Customer Feedback. For customer feedback regarding product quality, MCS combines the feedback's results and the sensed information from a production process to track products, and if there is any problem with a product, the producer will obtain first-hand information to improve its quality. It is difficult to obtain user feedback using AI-based sensing and to track a product outside the production process.
  - ◦ Logistic Tracking. Logistic tracking is easy to achieve via human-carried devices.
  - ◦ Location. The life cycle of a product mainly consists of three stages: production, supply, and consumption. To track the life cycle and even monitor each stage, the location information is always very important. Because of its high degree of mobility and scalability, MCS can easily obtain the real-time location information of a product.

It is very difficult to say which type of sensing is absolutely better based on cost. For example, for full coverage, is the cost of human-carried mobile devices or robots lower? Salary needs to be paid to humans every month, while, for robots, initial purchase and scheduled maintenance are all that is needed.

With the evolution of industrial sensing, MCS is a feasible new technology in industrial spaces. A detailed discussion of potential benefits is shown in Table II.

The discussion of Table II is conducted from three typical requirements of industry on sensing: environmental monitoring, personal monitoring, and product monitoring. MCS-based methods are compared with traditional methods to determine how MCS can improve the performance of industrial sensing. Similar applications of urban MCS are provided, which can be used in industry and can satisfy the sensing requirements of industry. The detailed explanations for this discussion are

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2657820, IEEE Access

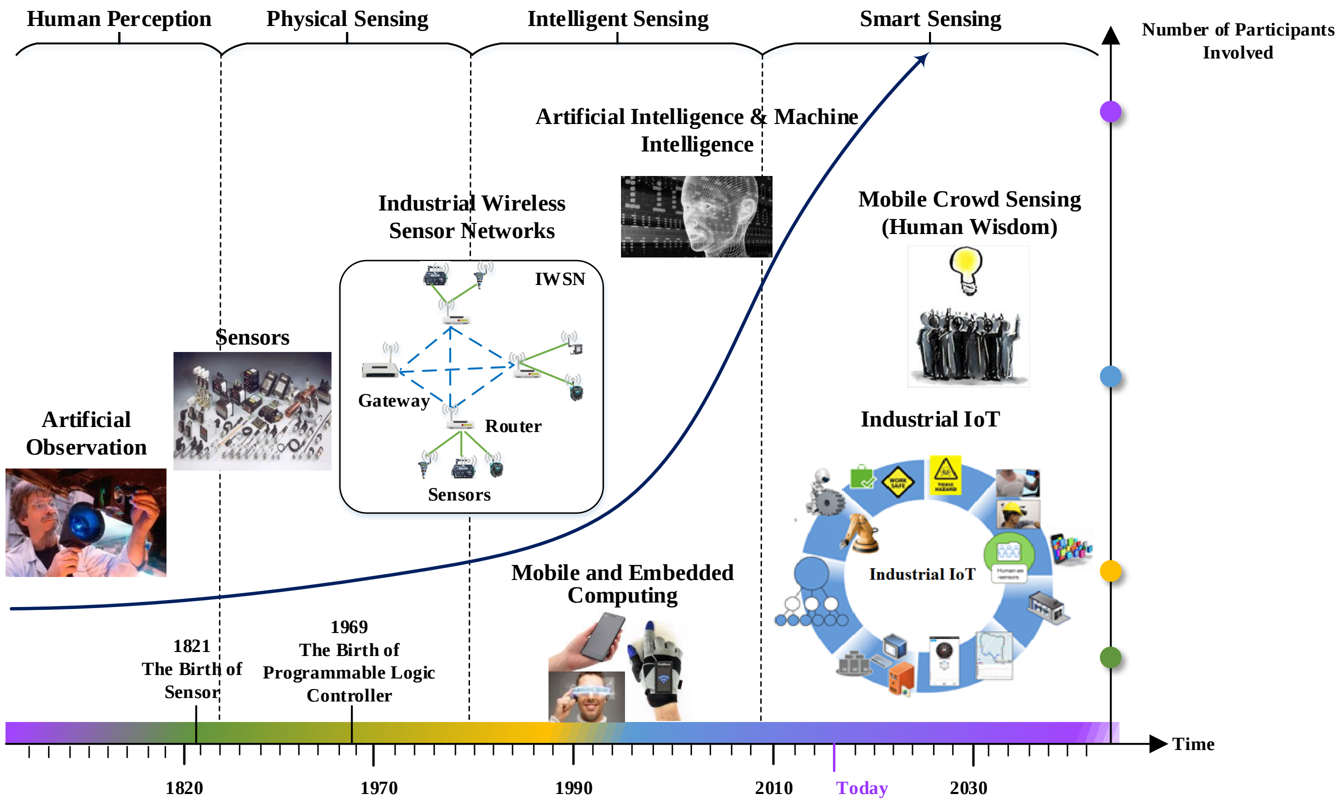


Fig. 2. Evolution of industrial sensing. With the evolution of (i) industrial requirements on sensing, and (ii) industrial devices, the sensing paradigm is gradually changing, and it can be divided into four stages. In different stages, different devices are used to support the corresponding sensing paradigm.

TABLE I. COST COMPARISON BETWEEN MCS AND AI-BASED SENSING IN INDUSTRIAL SPACES

Typical Industrial Requirement		MCS	AI-based Sensing
Environmental Monitoring	Full Coverage	Easy to obtain	Very hard
	Scalability	Easy	Very hard
	Mobility	Very easy	Less possible
Personal Monitoring	Health	Very easy	Not possible
	Location	Very easy	Not possible
Process Monitoring	Quality Checking	Not always possible	Easy to handle
	Asset Tracking	Easy	Possible
	Location	Easy	Possible
Product Monitoring	Customer Feedback	Very easy	Very hard
	Logistic Tracking	Easy	Not possible
	Location	Easy	Very hard

as follows:

- Environmental Monitoring
  - Traditional Method. Static sensor nodes and special devices are widely used to monitor areas of interest.
  - MCS-Based Method. Communications-enabled

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2657820, IEEE Access

TABLE II. MCS MEETS INDUSTRY

Typical Industrial Requirement	Traditional Method	MCS-Based Method	Available Similar Application in Urban MCS (the similar application of urban spaces can be learned by the application of industrial MCS)
Environmental Monitoring	Static sensor nodes and special devices	Communications-enabled mobile devices	[Public infrastructure construction] Environmental Monitoring
Personal Monitoring	None	Monitored anywhere and at any time	[Personal daily life] Personal Health Monitoring and Healthcare
Product Monitoring	Expert based	User-feedback based	[Personal daily life] Social Media

mobile devices are carried by humans to monitor the environment around them anywhere and at any time.
    - Available Similar Application in Urban MCS: Environmental monitoring [belongs to this classification: public infrastructure construction].
- Personal Monitoring
    - Traditional Method. In traditional industry, there is no such monitoring that can be used to monitor personal health and behavior.
    - MCS-Based Method. Personal health and behavior can be monitored anywhere at any time by using human-carried mobile devices. These devices are GPS-enabled.
    - Available Similar Application in Urban MCS. Personal health monitoring and healthcare [belongs to this classification: personal daily life].
- Product Monitoring
    - Traditional Method. Experts are used to track the production process to guarantee the quality of products. The effectiveness of such tracking depends strongly on the experience and ability of the experts.
    - MCS-Based Method. User feedback is easy to submit to producers, and the users clearly know which points are not good for a product through daily use. Combining the users' feedback, it is easy to achieve product monitoring for improving product quality.
    - Available Similar Application in Urban MCS. Social media [belongs to this classification: personal daily life]. This application can be used directly to obtain user feedback about a product.

IV. POTENTIAL INDUSTRIAL APPLICATIONS AND OPEN ISSUES

A. Potential Industrial Applications

Figure 3 illustrates the potential MCS applications in industrial spaces. MCS enables the industrial value chain to be more efficient, and it fully integrates suppliers, producers, and customers. Moreover, it enables collaborative sensing between humans and between humans and machines. As a further step, Big Data as a Service (BDaaS) can be achieved to help producers, suppliers, and customers understand and use insights learned from large amounts of sensing data in order to obtain competitive advantages and design better user experiences.

The industrial value chain consists of three main components: producers, suppliers, and customers: (i) producers, for which 41% of technology sectors will be the automation technology based on the full connection between humans and machines in Industry 4.0 [38]; (ii) suppliers, for which the connection among humans (carrying mobile phones) and products (with embedded RFID tags) allows factories to gain end-to-end visibility of their supply chains; and (iii) customers. By connecting customers and producers, customers will be at the center of the changes to value chains, products, and services. These three components of the industrial value chain produce very large amounts of heterogeneous data from humans and various machines. Such data can be used to help producers, suppliers, and customers understand and use insights mined from this very large amount of sensing data. On this basis, BDaaS can be achieved to: (i) manage production, products, and humans; (ii) share various data from different aspects, e.g., production, logstics, storage, marketing, and environment; and (iii) connect machines, products, and humans.

Three components and the corresponding internal process are connected by the connected machines, products, and humans. Various sensing data from these machines, products, and humans can be shared and integrated by MCS. The data are closely related to production, logistics, storage, marketing, and environment. Through the integrated data, industrial production, products, and humans can be remotely monitored, updated, and controlled.

Traditionally, the three components of the industrial value chain and the corresponding internal processes are comparatively independent of each other, and it is difficult to achieve a full connection between different components and internal processes using traditional methods.

- Producers. There are three internal processes for producers: production, storage, and logistics. In the traditional industrial methods, there are no strong relationships between these three processes. They cannot clearly know each other. For example, the production process cannot obtain information about storage and logistics in a real-time way in order to adjust online production.
- Suppliers. In traditional industrial methods, it is difficult to make the supply chain visible to each concerned participant. End-to-end visibility of supply chains can help producers improve production effectiveness.
- Customers. Customer feedback is difficult for producers to receive in the traditional industrial model. First-

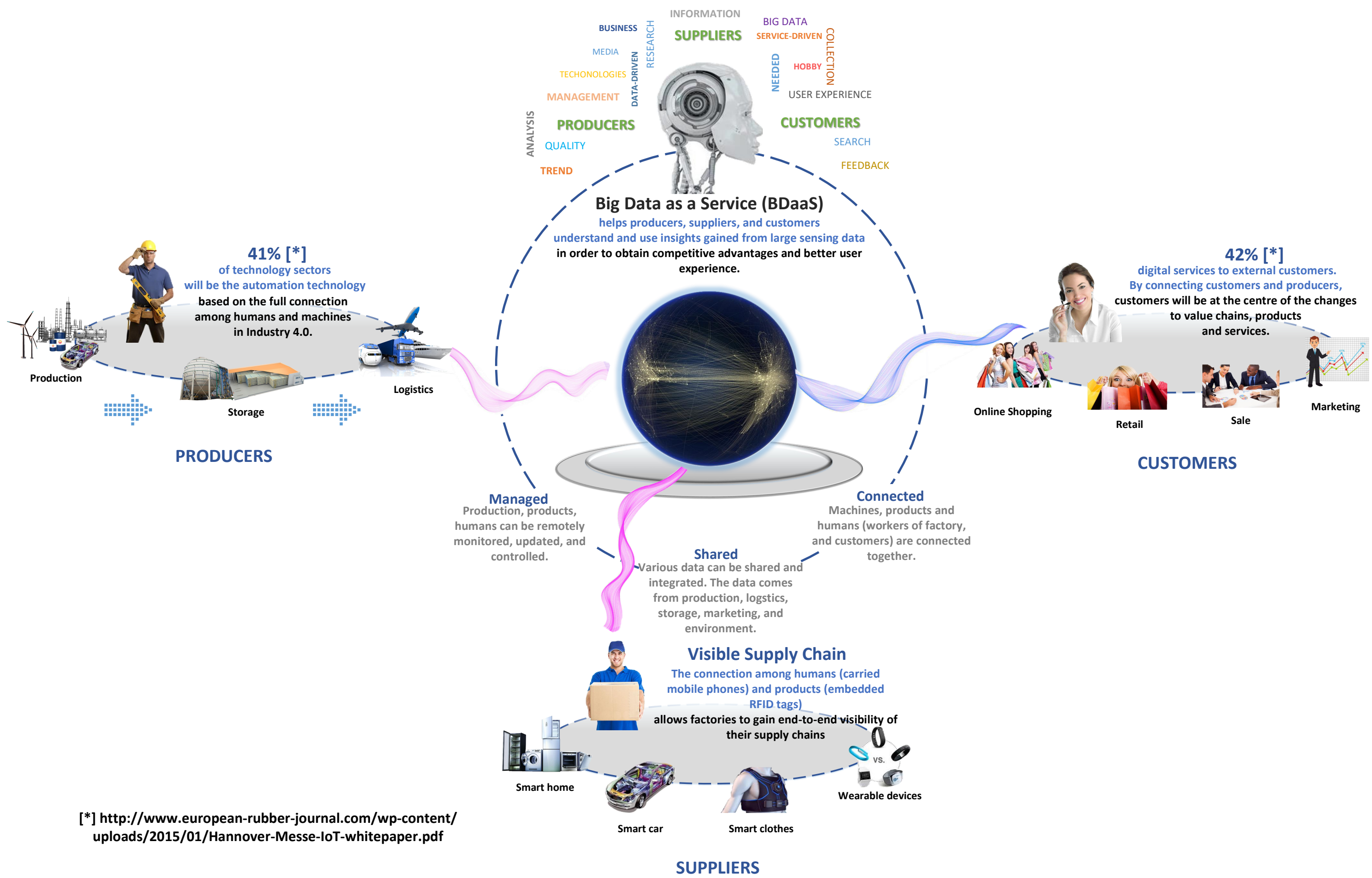


Fig. 3. Framework of MCS in industrial spaces. Mobile crowd sensing is used for a more connected industrial mode. Industrial MCS fully integrates suppliers, producers, and customers, and enables collaborative sensing between humans and between human and machine.

hand customer information is very important to improve the quality of products in a timely manner, and avoid economic losses.

The foregoing descriptions of problems reveal the inadequacy of using traditional methods to solve them. MCS opens up new possibilities by providing a flexible, scalable, and cost-effective method for effectively solving such industrial issues.

B. Open Issues

There are still many limitations and open issues for this emerging MCS applications in industrial spaces. These are also the unique challenges that should be studied for industrial MCS:

Integration of MCS and static sensing. Although traditional sensor networks have higher cost and poorer scalability, they often have a more reliable sensing quality, which can be used to compensate for inadequate sensing opportunities provided solely by a MCS system. These traditional sensor networks can be combined to constitute industrial IoT. Such IoT consists of various sensors to achieve machine intelligence. Since sensing opportunities are imbalanced among different regions, it is important to study where to deploy, and how many, specialized sensor nodes, and how to collaborate with mobile nodes to achieve the required sensing quality.

Balance between sensing quality and privacy. Much private information from participants will be leaked during sensing; for example, the location information of participants. The location is important information for improving the sensing quality; for example, if there is no location information for environmental monitoring, such monitoring is meaningless, and the specific physical meaning of the sensed data will be very difficult to understand.

Stability of the connectivity between different devices. The connectivity of all devices is important to achieving full coverage for sensing. For example, if all devices are connected to form a network to monitor an area of interest, if some devices fail, the connectivity of the network will be impacted, and parts of the information from the area of interest will be lost.

Consistency of communication protocols between different devices. Compared to urban MCS, industrial MCS extends the devices which are used in sensing to include not just mobile phones. Different devices can support different communication protocols based on their different application requirements. For example, if a ZigBee-based sensor node wants to communicate with a mobile phone, more extension components are needed. The consistency of communication protocols can help us easily obtain data synchronization and the time sequence of sensing data can help us track the evolution of an event. This time sequence can be obtained by strict data synchronization submitted by different devices.

V. Conclusions

This paper reviewed and classified the novel studies of urban MCS, and by investigating the evolution of industrial sensing, MCS has been proposed to achieve the integration of human wisdom and machine intelligence in industrial spaces. Based on such an integration, the benefits that MCS can bring have been illuminated by comparing MCS-based methods with industrial traditional methods. Keyed to the benefits of MCS, the potential applications of industrial MCS have been discussed from the three main components of the industrial value chain: producers, suppliers, and customers. Upon comparing the benefits of MCS with the inadequacies of traditional methods in industrial spaces, it has been shown that MCS can provide a flexible, scalable, and cost-effective method for industrial sensing, and can, furthermore, achieve the full connection of the three main parts of the industrial value chain.

Acknowledgements

This work was supported by the 2013 Special Fund of Guangdong Higher School Talent Recruitment, Educational Commission of Guangdong Province, China (Project No: 2013KJCX0131), by the Guangdong High-Tech Development Fund (No: 2013B010401035), and by the National Natural Science Foundation of China (Grant No. 61401107).

References

[1] H. Ma, D. Zhao, and P. Yuan, "Opportunities in mobile crowd sensing," *IEEE Communications Magazine*, vol. 52, no. 8, pp. 29–35, 2014.

[2] R. K. Ganti, F. Ye, and H. Lei, "Mobile crowdsensing: current state and future challenges." *IEEE Communications Magazine*, vol. 49, no. 11, pp. 32–39, 2011.

[3] P. Dutta, P. M. Aoki, N. Kumar, A. Mainwaring, C. Myers, W. Willett, and A. Woodruff, "Common sense: participatory urban sensing using a network of handheld air quality monitors," in *Proceedings of the 7th ACM conference on embedded networked sensor systems*. ACM, 2009, pp. 349–350.

[4] X. Hu, X. Li, E. C.-H. Ngai, V. C. Leung, and P. Kruchten, "Multidimensional context-aware social network architecture for mobile crowdsensing," *IEEE Communications Magazine*, vol. 52, no. 6, pp. 78–87, 2014.

[5] H. Roitman, J. Mamou, S. Mehta, A. Satt, and L. Subramaniam, "Harnessing the crowds for smart city sensing," in *Proceedings of the 1st international workshop on Multimodal crowd sensing*. ACM, 2012, pp. 17–18.

[6] B. Pan, Y. Zheng, D. Wilkie, and C. Shahabi, "Crowd sensing of traffic anomalies based on human mobility and social media," in *Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM, 2013, pp. 344–353.

[7] V. Freschi, S. Delpriori, L. C. Klopfenstein, E. Lattanzi, G. Luchetti, and A. Bogliolo, "Geospatial data aggregation and reduction in vehicular sensing applications: the case of road surface monitoring," in *2014 International Conference on Connected Vehicles and Expo (ICCVE)*. IEEE, 2014, pp. 711–716.

[8] P. Huang and J. Zhang, "Facts related to august 12, 2015 explosion accident in tianjin, china," *Process Safety Progress*, vol. 34, no. 4, pp. 313–314, 2015.

[9] B. Guo, Z. Wang, Z. Yu, Y. Wang, N. Y. Yen, R. Huang, and X. Zhou, "Mobile crowd sensing and computing: The review of an emerging human-powered sensing paradigm," *ACM Computing Surveys (CSUR)*, vol. 48, no. 1, p. 7, 2015.

[10] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 1, pp. 1–12, 2010.

[11] G. Cardone, A. Cirri, A. Corradi, and L. Foschini, "The participact mobile crowd sensing living lab: The testbed for smart cities," *IEEE Communications Magazine*, vol. 52, no. 10, pp. 78–85, 2014.

[12] M. A. Bochicchio, M. Zappatore, and A. Longo, "Using mobile crowd sensing to teach technology and entrepreneurship in high schools: An experience from southern italy," in *2015 IEEE Global Engineering Education Conference (EDUCON)*. IEEE, 2015, pp. 948–953.

[13] X. Zhang, Z. Yang, W. Sun, Y. Liu, S. Tang, K. Xing, and X. Mao, "Incentives for mobile crowd sensing: A survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 54–67, 2016.

[14] J. Ren, Y. Zhang, K. Zhang, and X. Shen, "Exploiting mobile crowdsourcing for pervasive cloud services: challenges and solutions," *IEEE Communications Magazine*, vol. 53, no. 3, pp. 98–105, 2015.

[15] B. Guo, C. Chen, D. Zhang, Z. Yu, and A. Chin, "Mobile crowd sensing and computing: when participatory sensing meets participatory social media," *IEEE Communications Magazine*, vol. 54, no. 2, pp. 131–137, 2016.

[16] V. Pankratius, F. Lind, A. Coster, P. Erickson, and J. Semeter, "Mobile crowd sensing in space weather monitoring: the mahali project," *IEEE Communications Magazine*, vol. 52, no. 8, pp. 22–28, 2014.

[17] A. Salfinger, S. Girtelschmid, B. Pröll, W. Retschitzegger, and W. Schwinger, "Crowd-sensing meets situation awareness: A research roadmap for crisis management," in *System Sciences (HICSS), 2015 48th Hawaii International Conference on*. IEEE, 2015, pp. 153–162.

[18] C. Capineri, M. Haklay, H. Huang, V. Antoniou, J. Kettunen, F. Ostermann, and R. Purves, "European handbook of crowdsourced geographic information," 2016.

[19] A. Dobra, N. E. Williams, and N. Eagle, "Spatiotemporal detection of unusual human population behavior using mobile phone data," *PloS one*, vol. 10, no. 3, p. e0120449, 2015.

[20] J. Wan, J. Liu, Z. Shao, A. V. Vasilakos, M. Imran, and K. Zhou, "Mobile crowd sensing for traffic prediction in internet of vehicles," *Sensors*, vol. 16, no. 1, p. 88, 2016.

[21] A. Tamilin, I. Carreras, E. Ssebaggala, A. Opira, and N. Conci, "Context-aware mobile crowdsourcing." in *UbiComp*, 2012, pp. 717–720.

[22] Q. Han, S. Liang, and H. Zhang, "Mobile cloud sensing, big data, and 5g networks make an intelligent and smart world," *IEEE Network*, vol. 29, no. 2, pp. 40–45, 2015.

[23] F. Calabrese, M. Diao, G. Di Lorenzo, J. Ferreira, and C. Ratti, "Understanding individual mobility patterns from urban sensing data: A mobile phone trace example," *Transportation research part C: emerging technologies*, vol. 26, pp. 301–313, 2013.

[24] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell, "A survey of mobile phone sensing," *IEEE Communications magazine*, vol. 48, no. 9, pp. 140–150, 2010.

[25] A. Krause, E. Horvitz, A. Kansal, and F. Zhao, "Toward community sensing," in *Proceedings of the 7th international conference on Infor-*

mation processing in sensor networks. IEEE Computer Society, 2008, pp. 481–492.

[26] E. Macias, A. Suarez, and J. Lloret, "Mobile sensing systems," *Sensors*, vol. 13, no. 12, pp. 17 292–17 321, 2013.

[27] K. Yang, K. Zhang, J. Ren, and X. Shen, "Security and privacy in mobile crowdsourcing networks: challenges and opportunities," *IEEE Communications Magazine*, vol. 53, no. 8, pp. 75–81, 2015.

[28] D. He, S. Chan, and M. Guizani, "User privacy and data trustworthiness in mobile crowd sensing," *IEEE Wireless Communications*, vol. 22, no. 1, pp. 28–34, 2015.

[29] B. Guo, H. Chen, Q. Han, Z. Yu, D. Zhang, and Y. Wang, "Worker-contributed data utility measurement for visual crowdsensing systems," *IEEE Transactions on Mobile Computing*, 2016.

[30] B. Guo, H. Chen, Z. Yu, W. Nan, X. Xie, D. Zhang, and X. Zhou, "Taskme: toward a dynamic and quality-enhanced incentive mechanism for mobile crowd sensing," *International Journal of Human-Computer Studies*, 2016.

[31] Y. Chon, N. D. Lane, Y. Kim, F. Zhao, and H. Cha, "Understanding the coverage and scalability of place-centric crowdsensing," in *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*. ACM, 2013, pp. 3–12.

[32] L. G. Jaimes, I. J. Vergara-Laurens, and A. Raij, "A survey of incentive techniques for mobile crowd sensing," *IEEE Internet of Things Journal*, vol. 2, no. 5, pp. 370–380, 2015.

[33] L. Da Xu, W. He, and S. Li, "Internet of things in industries: A survey," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 4, pp. 2233–2243, 2014.

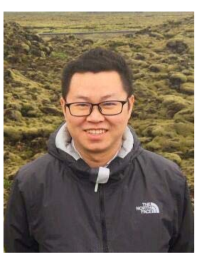
[34] V. Ç. Güngör and G. P. Hancke, *Industrial wireless sensor networks: Applications, protocols, and standards*. Crc Press, 2013.

[35] S. Rahman, "Artificial intelligence in electric power systems: a survey of the japanese industry," *IEEE Transactions on Power Systems*, vol. 8, no. 3, pp. 1211–1218, 1993.

[36] J. Liu, H. Shen, and X. Zhang, "A survey of mobile crowdsensing techniques: A critical component for the internet of things," in *Computer Communication and Networks (ICCCN), 2016 25th International Conference on*. IEEE, 2016, pp. 1–6.

[37] D. P. Jones, *Biomedical sensors*. Momentum press, 2010.

[38] R. Drath and A. Horch, "Industrie 4.0: Hit or hype?" *IEEE industrial electronics magazine*, vol. 8, no. 2, pp. 56–58, 2014.



Lei Shu (M'07-SM'15) is a Lincoln Professor of University of Lincoln, UK and a Distinguished Professor in Guangdong University of Petrochemical Technology. He is also the executive director of Guangdong Provincial Key Laboratory of Petrochemical Equipment Fault Diagnosis, China. His main research field is Wireless Sensor Networks. He has published over 300 papers in related conferences, journals, and books in the area of sensor networks. He had been awarded the Globecom 2010 and ICC 2013 Best Paper Award. He has been serving as Editor-in-Chief for EAI Endorsed Transactions on Industrial Networks and Intelligent Systems, and associate editors for IEEE Systems Journal, IEEE Access, etc. He has served as more than 50 various Co-Chair for international conferences/workshops, e.g., IWCMC, ICC, ISCC, ICNC, Chinacom, especially Symposium Co-Chair for IWCMC 2012, ICC 2012, General Co-Chair for Chinacom 2014, Qshine 2015, Collaboratecom 2017, Mobiquitous2018, Steering and TPC Chair for InisCom 2015; TPC members of more than 150 conferences, e.g., ICDCS, DCOSS, MASS, ICC, Globecom, ICCCN, WCNC, ISCC.

Yuanfang Chen (S'09-M'13) received her Ph.D. degree and M.S. degree from Dalian University of Technology, China. She currently works in Guangdong University of Petrochemical Technology as a Senior Researcher. She was an assistant researcher of Illinois Institute of Technology, U.S.A. with Prof. Xiang-Yang Li, from 2009 to 2010. She had been awarded the MASS 2009, 2013 IEEE Travel Grant, SIGCOMM 2013 Travel Grant, IWCMC 2009 and MSN 2010 Invited Paper. She has served as volunteer of MobiCom & MobiHoc 2010 and IEA-AIE 2012. She has been invited as the Session Chair of some good conferences, e.g., MobiQuitous 2013, ICA3PP 2015, and the TPC member, e.g., Globecom 2014, MobiApps 2014. She has served as the fixed reviewer of some top journals and conferences, e.g., IEEE Transactions on Industrial Informatics, ACM Computing Surveys, IEEE Transactions on Fuzzy Systems and Ad Hoc & Sensor Wireless Networks. She is an associate editor of EAI Endrosed Transactions on Industrial Networks and Intelligent Systems. Her research interests include localization, energy optimization, machine learning, algorithm design, and wireless sensor networks.

Zhiqiang Huo is currently working towards his Ph.D. degree at University of Lincoln, UK. He received his Ms. and BS. From China University of Geosciences Beijing, China in 2016 and 2013 respectively. His field of interest is mechanical fault diagnosis, mobile crowdsensing, middleware in wireless sensor networks.

Neil Bergmann has been Professor of Embedded Systems in the School of Information Technology and Electrical Engineering at The University of Queensland, Brisbane Australia since 2001. He received BSc (Computer Science), and BE (Electrical Engineering) degrees from University of Queensland in 1980, and completed his Ph.D. in Computer Science at University of Edinburgh, UK, in 1984 in the area of CAD for VLSI. His current research interests are in embedded systems, especially reconfigurable System-on-Chip technology, and also in Wireless Sensor Networks.

Lei Wang is currently a full professor of the School of Software, Dalian University of Technology, China. He received his B.S., M.S. and Ph.D. from Tianjin University, China, in 1995, 1998, and 2001, respectively. He was a Member of Technical Staff with Bell Labs Research China (2001-2004), a senior researcher with Samsung, South Korea (2004-2006), a research scientist with Seoul National University (2006-2007), and a research associate with Washington State University, Vancouver, WA, USA (2007-2008). His research interests involve wireless ad hoc network, sensor network, social network and network security. He has published 70+ papers and the papers have 1000+ citations. He is a member of the IEEE, ACM and a senior member of the China Computer Federation (CCF).